Setting up a framework for model predictive control with moving horizon state estimation using JModelica.org

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Conclusions

- ☑ Using **Moving Horizon State Estimation (MHE)** in a **Model Predictive Control (MPC)** framework for Modelica models using JModelica.org improves building heating control.
- ☑ The covariance of every controller model's time series is important for the state estimation. These covariances can be retrieved from the data-driven parameter estimation of the controller models.

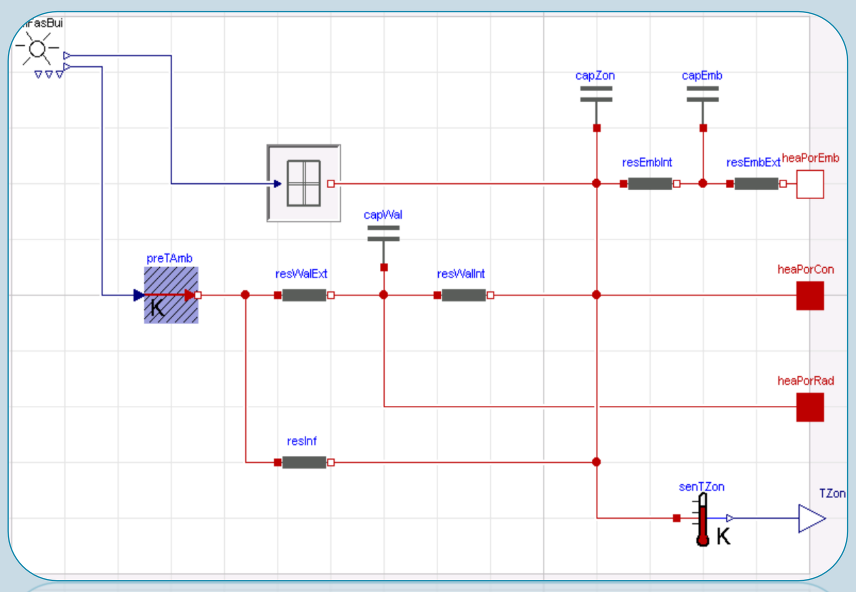
Aim

- ➔ Use **a stochastic modelling approach in Modelica** models, in order to apply state estimation to controller models.
- ➔ Integrate state estimation in an MPC framework.

Introduction

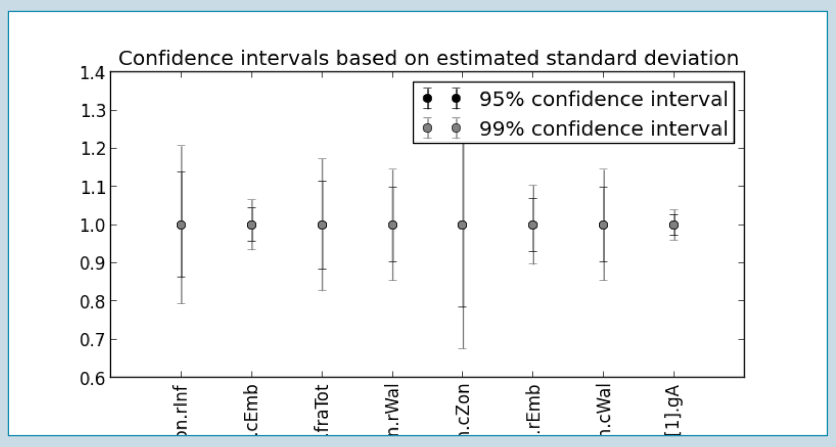
The **heating of a building** can be controlled using **MPC**. The **controller model** should be carefully selected and parameterized, which is done using Modelica model-formulations and a toolbox for parameter estimation. Since a (low order) controller model is used to control a detailed emulator model or a real building, a one-to-one coupling with measurements is not possible. Therefore, a **state estimator** is implemented using a **Moving Horizon Estimation (MHE)** scheme.

	Par	Val
Capacitance [J/K]	cEmb	6.4e7
	cWal	3.6e7
	cZon	8.3e6
Resistance [K/W]	rEmb	.0003
	rWal	.011
	rInf	.032
Irr [m²]	gA	9.3



Controller model: RC model zone

Parameter estimation: The confidence intervals for the grey-box parameters in the different intervals computed with the covariance, assuming a normal distribution. These covariance can Be can used in the objective function of the state estimator



Process noise

MHE estimates the controller model error, on the states, based on a (limited) number of measured states (here only T_{zone}). The error represents the process noise which is added to the state equations as a stochastic heat flux.

- Near the end, the states change rapidly to improve the objective function. This mathematical optimum is not physical, which reflects in jumps in the MPC(OCP) results after state updates.

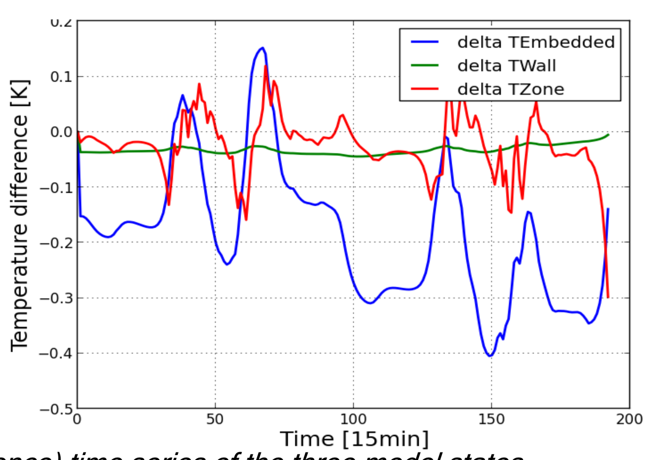
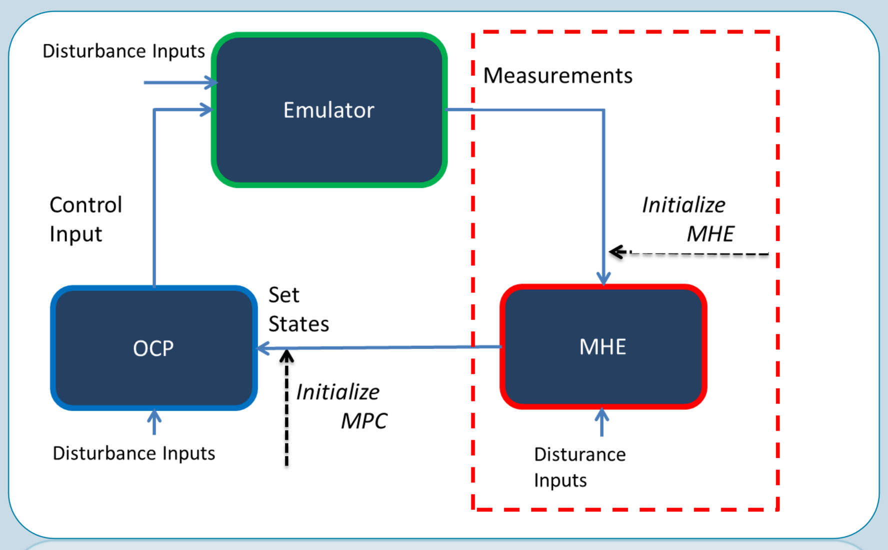


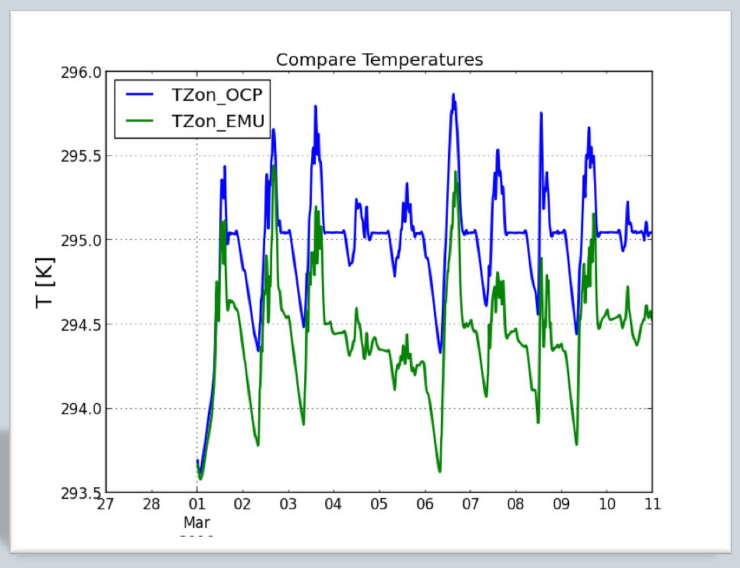
Fig P1: process error (temperature difference) time series of the three model states



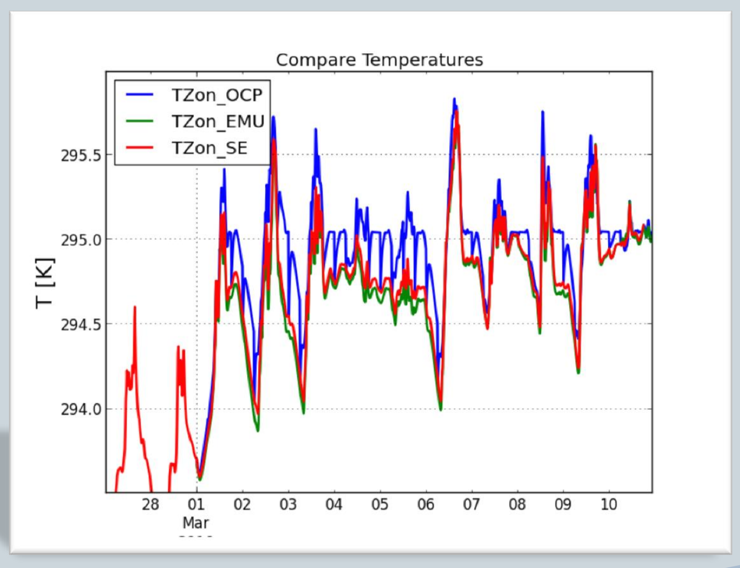
Outline framework

Results

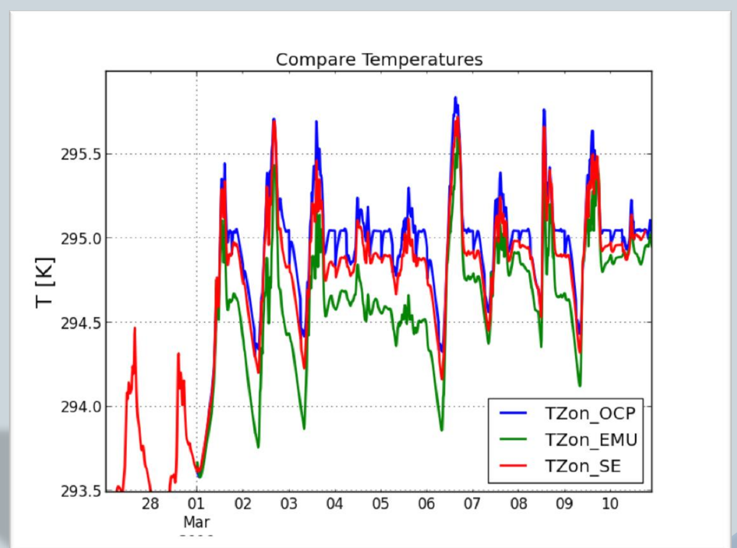
- The MPC framework is tested for a period of 10 days in March 2010 to control heating setpoints of a detailed single zone building model.
- The optimal controller minimizes a multi-objective cost function which weights energy cost vs. discomfort (modelled with no cost inside a comfort band and a quadratic cost outside of the band)



MPC1: without state estimation.
The controller model (OCP) is unaware of the true state (EMU)



MPC2 with state estimation.
High (relative) reliance on measurements ($R^{-1}/Q^{-1} = 10$), the controlled building (EMU) is closer to the controller optimal set temperature (OCP)



MPC3 with state estimation.
low (relative) reliance on measurements ($R^{-1}/Q^{-1} = 1$), the controlled building (EMU) is further away from the controller optimal set temperature (OCP).

Framework

Initialize **state estimator** (SE)	: simulation (fmu)
Estimate states (process noise)	: optimization (fmux)
Initialize **optimal controller** (OCP)	: simulation (fmu)
Optimize control	: optimization (fmux)
Apply controls (**EMU**: detailed simulation/real building)	
Measure outputs	

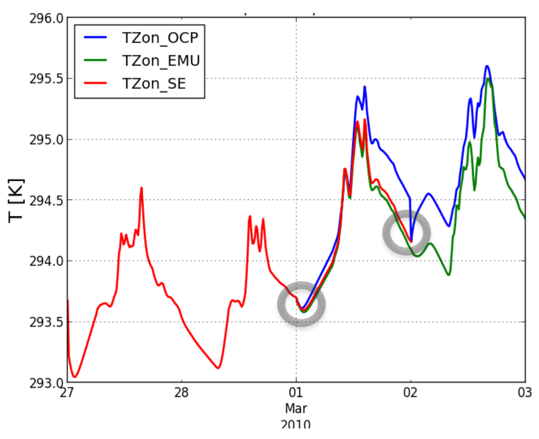


Fig. F1: zone temperature (estimate, optimal and real)
- *At the indicated points, the controller model is updated with the state estimator (SE) results.*
- *The controller model (OCP) reacts to sudden state change.*
- *The emulator model (EMU) follows partly.*

State estimation:

- Stochastic model to represent proces noise:

$$\dot{x} = f(x,u) + \dot{w}$$
$$y = g(x,u) + v$$

- Moving Horizon Estimator (no arrival cost)

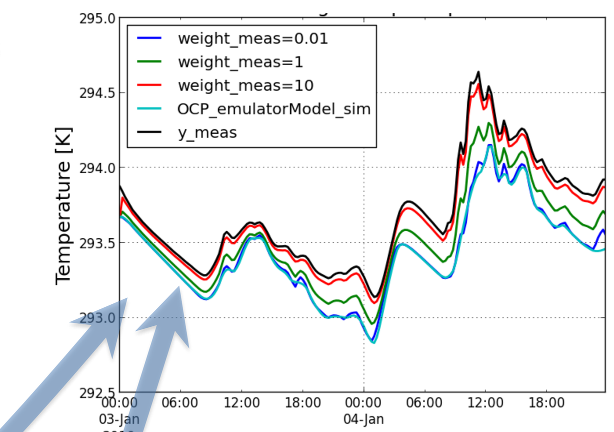
$$obj_{MHE} = \min_{x0,\{w_k\}_{k=T-N}^{T-1}} \sum_{k=T-N}^{T-1} \|v_k\|^2_{R^{-1}} + \|w_k\|^2_{Q^{-1}} + \underbrace{\cancel{\|x_{T-N} - \overline{x_{T-N}}\|^2_{P_0^{-1}}}}_{\text{Arrival cost}}$$
$$= \min_{\{w_k\}_{k=0}^{T-1}} \sum_{k=T-N}^{T-1} \|y_{meas_k} - g(x_k,u_k)\|^2_{R^{-1}} + \|x_{k+1} - f(x_k,u_k)\|^2_{Q^{-1}}$$

- **Output fitting** term (TZon)
- R = covariance matrix of the output measurements

- **Process noise** term (TZon, TWal, TEmb)
- Q = covariance matrix of the states.

Larger covariance ➔smaller influence in the objective

Covariance matrices R and Q
- Tuning parameter
or
- From grey-box parameter estimation



- *Fig. F2: influence of $weight_{meas} = R^{-1}/Q^{-1}$ value: large R^{-1}/Q^{-1} closer to model ($OCP_{emulatorModelsim}$), small R^{-1}/Q^{-1}, closer to measurement (y_{meas})*

Modelica stochastic state model

```
model Capacitor_sto "Stochastic lumped thermal capacity"
  parameter Modelica.SIunits.HeatCapacity c
    "Heat capacity of element (= cp*m)";
  Modelica.Thermal.HeatTransfer.Interfaces.HeatPort_a heaPor;
  input Real der_w;
  Modelica.SIunits.TemperatureDifference w(start=0);
equation
  der(w) = der_w;
  c*der(heaPor.T) = heaPor.Q_flow + c*der_w;
end Capacitor_sto;
```

Process noise

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